Karlsruhe Institute of Technology

Online Neural Network-based Language Identification

Master's Thesis
Daniel H. Draper

INTERACTIVE SYSTEMS LAB - INSTITUTE FOR ANTHROPOMATICS AND ROBOTICS

Contents

Motivation

- ASR and SLT commercially great success [”OK, Google“, Siri, Jibbigo]
- Best performing ASR models are still trained on one source language.[1]

- Performance increase for multilingual tasks[1], UI streamlining.

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Specific Applications

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Lecture Translator

- Low latency, online application
- Small source language amount make performance increase likely

European Parliament

- Attempts to replace translators with SLT [2]
- Many languages challenging, great potential.

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Related Work

Non-NN-Approaches

- single-language phone recognition followed by language-dependent, interpolated n-gram language modeling (PRLM)[3]
- multiple single-language phone recognizers and language-dependent parallel phone recognition (PPRM)[3]
- Gaussian Mixture Models (GMM)s [4]
- Vector Space Modelling + PPRM[5]
- I-Vector approaches[6][7]

Related Work II/Based on

Similar Approaches

- Matejka et. al[8] similar setup: BNF $\rightarrow$ LID, with averaging 5 LID nets.
- [9] M. Heck et al. evaluate LID approaches prospect of Lecture Translator integration: PPRM/PRLM + Hybrid.

- Markus [10]: ”Language Adaptive DNNs for Improved Low Resource Speech Recognition“, experimental setup very similar (LFV/LID)

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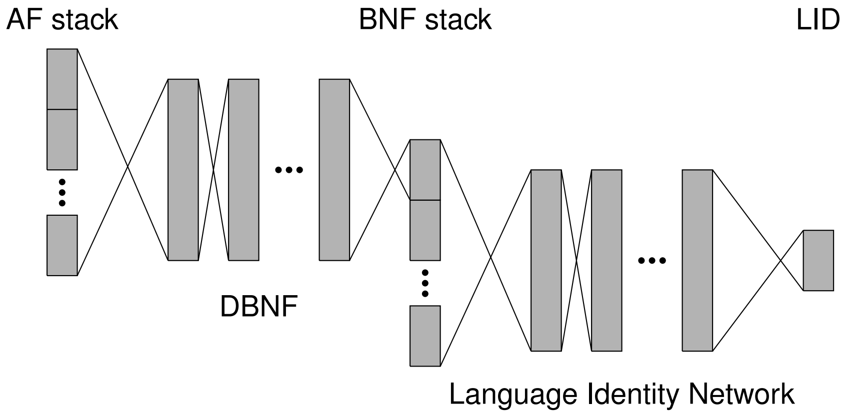
Experimental Setup



Data Sets

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Euronews 2014

- 10 Languages (EN, FR, DE, AR, ES, IT, PO, PT, RU, TR)
- Original Corpus: 72h / Language, Reduced corpus: 18h / Language (Random Sampling of 10.000 speakers)
- 80 % train data, 10 % each dev/test set

Lecture Data

- 3 Languages (EN, FR, DE) ≈10h per language.
- KIT lectures, InterACT25, DGA talks
- Validation of Euronews results, “right” patterns learned (different environment)

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Data Sets II

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European Parliament

- 7 Languages (EN, FR, DE, ES, IT, PO, PT) 3.6h per language
- Simultaneous translation of all parliament speeches
- Further Validation, Proof-of-concept for Lecture Translator integration

Feature Extraction

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Feature Definition

- Samplerate: 16 kHz
- Standard Janus Capabilities:
  - POWER
  - IMEL
  - PITCH
  - TONE
- Context of 6 frames

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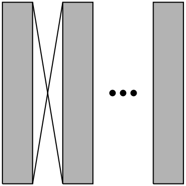

DBNF

DBNF

- AF Stack as input
- Targets context-dependent phoneme states
- 6 layers, each 1000 neurons
- BNF of 42 dimensions
- Stacked with context of 11 frames

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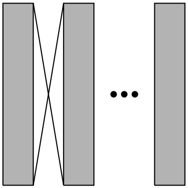

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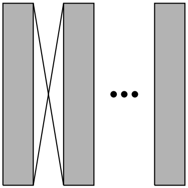

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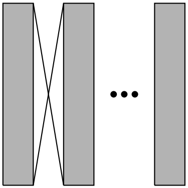

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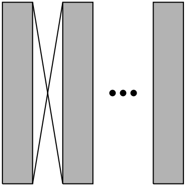

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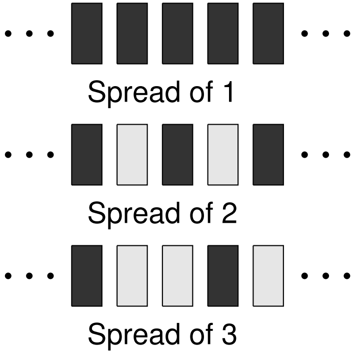

Spread Evaluation

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- Evaluation of spreads 4 and 5 for different nets on Euronews
- Spread of 3 outperforms 4 and 5, surprisingly 5 outperforms 4

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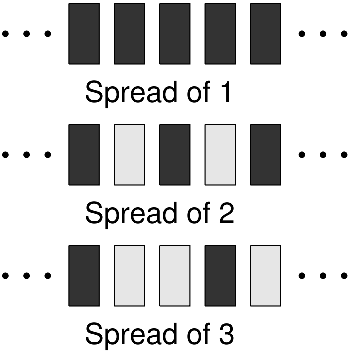

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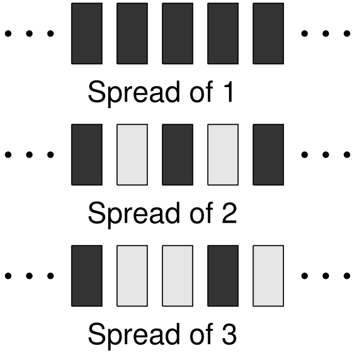

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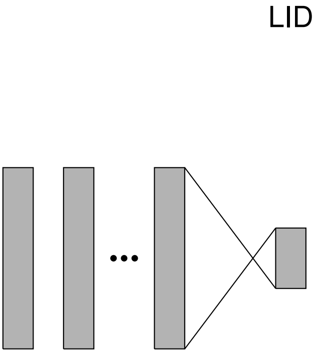
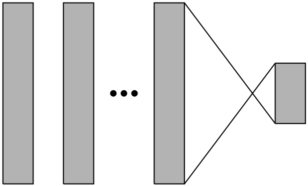


Baseline Setup

- BNF with context as input
- 5 layers of each 1000 neurons
- Tanh activation, mse loss function
- Mini-batches size 2,000,000, learning rate(lr) 0.01
- Retrained with 1000:10 layer with lr 1

DNN Structure

LID



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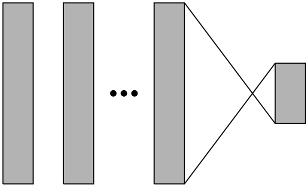

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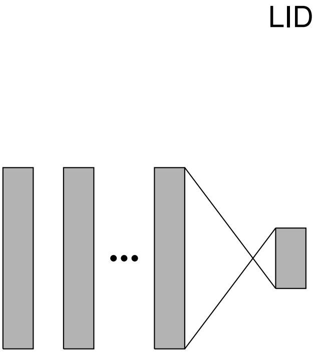

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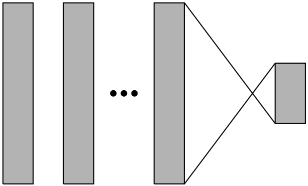

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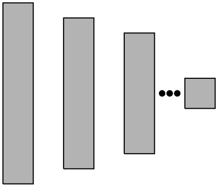

Other Evaluations

- Lower LR ✓
- Baseline add Layers ✗
- Tree net with 5 layers ✓
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- Tree net with $>$ 6 layers ✗ _
- Cross-Data-Set training ✓
- Concat-Set training ✓✓

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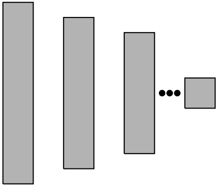

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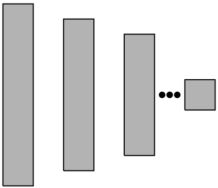

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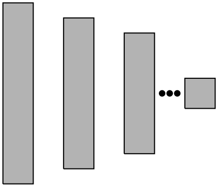

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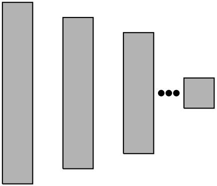

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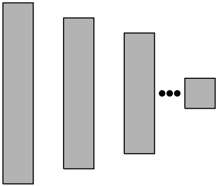

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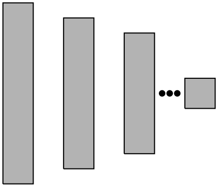

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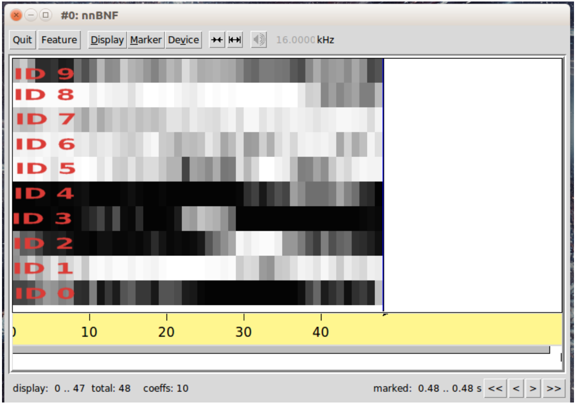
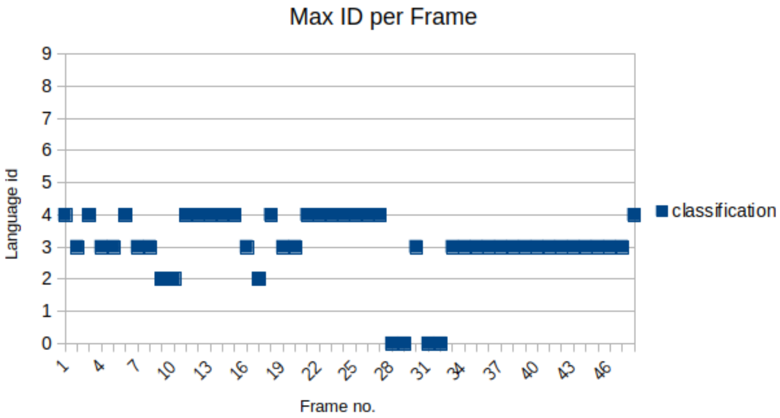


#0: nnBNF
Quit
Feature
Display
Marker
Device
16.0000 kHz
ID 9
ID 8
ID 7
ID 6
ID 5
ID 4
ID 3
ID 2
ID 1
ID 0
10
20
30
40
display: 0 .. 47 total: 48 coeffs: 10
marked: 0.48 .. 0.48 s

Output



Max ID per Frame
Language id
9
8
7
6
5
4
3
2
1
0
1
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
Frame no.
classification

Metrics

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Error Rate

- Count outputs per language per frame
- Max count == actual language → correct, false otherwise
- Metric is percentage of error per language

Out-Of-Language-Error (OLE)

- Same counting as before
- Sum up FALSELY (as not equal to max language) classified languages
- Metric of "Sureness" of output
- Example: 50 frames classified as DE, 10 as EN, 5 as FR: $(5+10)/(5+10+50) = 0.23$
- Average OLE per language

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Smoothing Filters

Approaches

- Counting Filter (count in window, in total as maximum only).
- Gaussian Filter (convolution with Gaussian kernel)
- Speech / Noise Filter
- Language Filter (If domain smaller than targets trained)
- Sequence Filter (longest sequence in window)
- Difference (Only count output if difference between 2 max is $>$ thresh
- Weighted Average (FILTER capability)

Results I

Filter	**Overall Error TEST**	**OLE TEST**
Bare Net	0.305	0.198
Gaussian Filter (WS 15)	**0.307**	0.176
Counting Filter (WS 100)	**0.307**	**0.006**
Best	**0.307**	**0.006**

Results II

- Euronews: Samples $>$ 500 ms: 16 % Error (10L)
- Lecture Data: 6.5 % Error (3L, concat with Euronews data)
- European Parliament: 35 % (7L, 3.5h/language)
- Post Processing: Counting, Gauss Filter promising, relative improvement OLE 97 %.

Demo (easy)

Play

Demo (easy)

Language	Number of Frames classified
English	1095
German	123
French	18
Total Error	0.11

Demo (difficult)

Play

Demo (difficult)

Karlsruhe Institute of Technology

Language	Number of Frames classified
English	435
German	53
French	99
Total Error	0.25

Future Work

- RNNs [11]
- Post-Processing promising, further validation or actual focus
- Actual integration into online-environment like LT

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Questions?

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- M. Heck, S. StÃ$\frac{1}{4}$ker, and A. Waibel, "A hybrid phonotactic language identification system with an svm back-end for simultaneous lecture translation," in *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, March 2012, pp. 4857–4860.

References IV

- M. MÃ¼ller, S. StÃ¼ker, and A. Waibel, “Language adaptive dnns for improved low resource speech recognition,” in *Proceedings of the 17th Annual Conference of the International Speech Communication Association (INTERSPEECH)*, San Francisco, USA, September 8-12 2016.
- J. Gonzalez-Dominguez, I. Lopez-Moreno, H. Sak, J. Gonzalez-Rodriguez, and P. J. Moreno, “Automatic language identification using long short-term memory recurrent neural networks,” in *Fifteenth Annual Conference of the International Speech Communication Association*, 2014.

References V

H. Li, B. Ma, and K. A. Lee, “Spoken language recognition: From fundamentals to practice,” *Proceedings of the IEEE*, vol. 101, no. 5, pp. 1136–1159, May 2013.

Theory of LID

- Given input $S = \{s(1), s(2), \ldots, s(T)\}$, $\{L_1, L_2, \ldots, L_N\}$

Formulation of LID Task[12]

$L^O = \arg\max_l p(S|L_l)$

With segmentation into phones υ (sequence Υ):

$L^O = \arg\max_l P(\Upsilon|L_l)$

With Viterbi decoding on set of phone models M:

$\Upsilon^O = \arg\max_\upsilon P(S|\upsilon, M)$

Combining last 2 equations:

$$\boxed{L^O = \arg\max_l \sum_{\forall\Upsilon} P(S|\Upsilon, M) P(\Upsilon|L_l)}$$

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